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# EARLY STRATEGIC GUIDANCE FOR HIGHER VOCATIONAL SCHOOL STUDENTS USING SUPPORT VECTOR MACHINES

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## ABSTRACT

Academic guidance and orientation is important for vocational schools. In this study, data set of vocational school students are obtained from student affairs central database. The data is filtered and gender, age, geographical region student came from, high-school type, a special high school score of vocational high school student that is used for entering vocational school without exam, and school registration type are taken as six inputs. Academic success and graduation length are the two outputs that are aimed to be predicted. Based on these chosen input and output information, a model is aimed to be developed in order to help advisors in improving academic success and shortening graduation length of their students. Support vector machines based artificial intelligence technique is used. Input sensitivity analyses are also conducted. It is seen from the analyses that academic success and graduation length are both highly affected by gender. Also, academic background has also effect on two outputs in different manners. From the analyses, it can be concluded that the advisors can orient or guide students based on the SVM outputs.

**Key Words:** Vocational schools, academic guidance, academic success, graduation length, support vector machines, input sensitivity.

## INTRODUCTION

Extracting potentially valuable information from databases is an important issue for different areas ranging from industry to medicine to education (Witten, Frank, & Hall, 2011). With the improvement in the storage and power of computer technologies, data mining terminology gain importance. Data mining can be used for different tasks as classification, estimation, segmentation or description (Luan, 2002). For schools, huge amount of data are being created and stored every hour when a school is in session. Therefore, data mining is also used for different levels of schools (Zalik, 2005). Then, a dynamic modeling approach is also used to predict performance of high school students (Camacho, Cortés, Micle, & Sánchez-Sánchez, 2013). In addition, Kardan et. al. (Kardan, Sadeghi, Ghidary, & Sani, 2013) considered the e-learning environment and provided an artificial neural network based method for improving the student satisfaction on online course selection.

The interactions between the school and student can happen in a variety of different meanings and efforts, and academic advising is a very important tool for encouraging the student for educational, career and life goals

(Young-Jones, Burt, Dixon, & Hawthorne, 2013). Vocational schools, on the other hand, have significant differences from engineering or other faculty students from different perspectives as student profile, education goals and course contents. Therefore, studies on vocational studies dissociate from other higher education areas. Vocational schools must consider the labor needs of the community they are living in, challenge to respond market demands and prepare students for vocational roles. In the rapidly developing information age, changing job profiles and need for multi-skilled personnel are increasing the importance of the quality of the education for vocational school students.

According to a commentary on assessment of vocational competence in higher education, we had some ways to determine these competences which concludes multiple interpretations. Firstly, as a broad way, it includes knowledge, attitudes, skills, social and motivational aspects and work-related contents. Secondly, as a small way, it can be seen in a cognitive way to refer to result of an individual learning (Gijbels, 2011). About comparing the students' perceived and actual competence in higher vocational education, a questionnaire based research was realized over 169 students (Baartman & Ruijs, 2011). Then a study which provided in a higher vocational education, the critical factors are influenced to examine the quality of assessment for purpose, comparability and fairness as strong points. Addition to this, the weak points are presented as reproducibility of decisions and development of self-regulated learning. At finally, the critical factors are represented the translation of competences into these daily lessons and the involvement of the work field (Baartman, Gulikers, & Dijkstra, 2013). A meta-analysis for determining specific strategies on self-regulated learning factors in increasing academic performance which are variables of cognitive, meta-cognitive and managerial strategies, motivational aspects, knowledge, characteristics, instrumental measures and subjects (Donker, Boer, Kostons, Ewijk, & Werf, 2014).

In most universities, students choose their courses and other activities with the help of an advisor. The advisors must guide to the students in a right way. For vocational student, the need and importance of advisor system is much more important. The class and racial differences, family problems, lower income, less motivation make it also difficult. Thus, early prediction of academic performance of students is important for advisors.

Vocational schools bring together school and workplace learning, which is an effective method for preparing young people for jobs and smoothing initial transitions into the labor market (OECD, 2011). In a vocational school the advisor must have a pedagogical skill and specific competence to help a student. However, in under-developed countries and some developing countries having a large young population, the amount of students in a school is too much to deeply analyze all the students. Therefore, it is straightforward method to use data mining and artificial intelligence techniques to first separate risky and non-risk students and give much more time to risky ones.

Admission to vocational schools has some differences in all countries. For instance, in Turkey, students who graduate from technical and vocational high schools may choose to enroll in an associate degree program as a continuation of the program they had completed, or a similar one, found in their own Professional and Technical Education District (PTED) without entering the central exam using their PTED score. This is known as the open admission and the student may enroll in a vocational school associate programs out of their region. Open admission placements are made by the Turkish Student Selection and Placement Center (SSPC) automation system. Also, students who graduate from other high schools can enter vocational high schools with SSPC central exam.

In this study, academic success and graduation length of newly coming vocational school students are predicted using artificial intelligence techniques. Support vector machines (SVM) are used and the advisors can orient or guide students based on the SVM outputs.

## MODEL

Neural networks work best when the nature of the data is nonlinear. Running neural networks may take a very long time due to back-propagation. Most neural networks rely on the process for the hidden layer to perform the summation and constantly adjust the weights until it reaches an optimal threshold, which then produces the outcome for a record (Garson, 2008). Main solution method of this study is Support Vector Machines (SVMs) which are first proposed by the idea of mapping the non-linear input vectors to a higher dimensional feature space that is designed as a linear decision surface (Cortes & Vapnik, 1995). The special characteristics of the decision surface create a high level of machine learning ability, and ability to use high dimensional data (Ben-Hur & Weston, 2010). SVMs have effective usage in both classification and regression problems.

In this study, there are two output variables to be predicted which are the grade point average (GPA) (in terms of four-point system) and graduation length (in terms of day). They are predicted separately by using two different multi-input single-output SVM structures. For these, the same six input variables are used that are gender (M/F), age (days), geographical region, high-school type, PTED score, and school registration type. The values and definitions of these inputs and outputs are given in Table 1.

The data set is composed of 1138 students' information taken from Student Affairs Database of a large-scale vocational school with population of about 3500 students, 32 full-time and 21 part-time lecturers. In this study, students graduated between years 2002-2006 are considered.

## METHOD

Firstly, considering a set of training data $\{(\mathbf{t}_1, y_1), ...., (\mathbf{t}_{Ntr}, y_{Ntr})\}$, where each $\mathbf{t}_i \subset \Re^n$ denotes the input space of the sample and has a corresponding target value $y_i \subset \Re$ for $i$=1,..., $N_{tr}$ where $N_{tr}$ corresponds to the size of the training data for in solution approach that is support vector regression (Campbell & Ying, 2011).

Table 1: Model Parameters

| Input Code | Variable Name | Type | Definition |
|---|---|---|---|
| inp1 | Gender | 1,2 | Male, Female |
| inp2 | Age | Days | |
| inp3 | Geographical region | 1, 2, 3, 4, 5, 6, 7, 8, 9 | Mediterranean, East Anatolia, Agean, Southeast Anatolia, Central Anatolia, Black Sea, Marmara, Cyprus, Others |
| inp4 | High-school type | 1, 2, 3, 4, 5, 6, 7, 8, 9, 10 | General, Open, Multi-program, Teacher training, Religious vocational, Trade vocational, Industrial vocational, Girls' vocational, Hotel management and Tourism vocational, Others |
| inp5 | PTED score | Real valued | |
| inp6 | School registration type | -1, +1 | Open admission, placement by examination |
| **Output** | **Variable Name** | **Type** | **Definition** |
| SVM-I output | GPA | Four-point system | [0,4] |
| SVM-II output | Graduation length | Days | |

## EPSILON-SVR ALGORITHM

The idea of regression problem is to determine a function that can approximate future values accurately. The generic SVR estimating function takes the form:

$$\hat{y}(\mathbf{t}_i) = \mathbf{w}^T \Phi(\mathbf{t}_i) + b \tag{1}$$

where $\mathbf{w}^T = [w_1 \ \cdots \ w_m] \in \Re^m$ and $b \in \Re$ are the coefficients of the regression curve and $\Phi$ is a non-linear transformation function from $n$-dimensional input space $\Re^n$ to an $m$-dimensional feature space $F$ where $n < m$. The epsilon-SVR algorithm finds the values of $\mathbf{w}$ and $b$ by minimizing the optimization problem given as

$$\begin{aligned} &\min_{\mathbf{w},b,\xi,\xi^*} \frac{1}{2}\mathbf{w}^T\mathbf{w} + C\sum_{i=1}^{N_{tr}}\left(\xi_i + \xi_i^*\right) \\ &s.t. \quad y(\mathbf{t}_i) - \hat{y}(\mathbf{t}_i) \le \varepsilon + \xi_i, \quad i = 1,2,\ldots,N_{tr} \\ &\qquad\ \ \hat{y}(\mathbf{t}_i) - y(\mathbf{t}_i) \le \varepsilon + \xi_i^*, \quad i = 1,2,\ldots,N_{tr} \\ &\qquad\ \ \xi, \xi_i^* \ge 0 \qquad\qquad i = 1,2,\ldots,N_{tr} \end{aligned} \tag{2}$$

where $\mathbf{w}^T\mathbf{w}$ is the structural risk and represents the model complexity, $\xi_i$ and $\xi_i^*$ are slack variables used to measure errors outside the $\varepsilon$-tube (Campbell & Ying, 2011). Thus, the primary formulation is translated to a dual one which is a quadratic programming problem. From the solution of this QP problem, by using the Kernel trick, the regression model as

$$\hat{y}(t) = \sum_{i=1}^{N_{tr}} \alpha_i K\left(\mathbf{t}_i, \mathbf{t}\right) + b \tag{3}$$

Where $\alpha_i$ are regression parameters obtained from the solution of the QP problem (Campbell & Ying, 2011) (Schölkopf & Smola, 2002).

## INPUT SENSITIVITY ANALYSIS

The SVM model using input sensitivity analysis can be both configured as a more effective model and purified from input data set that has low or no effect on classification or regression performance. Also, for newly developed models, reduced computational burden, less data in the input data set and ease of update is obtained. Input sensitivity analysis gives us the importance of each input on the output. Thus, In order to achieve this, the partial derivative of output with respect to each input is needed. Let us remember that the input-output relationship of the SVR model is

$$\hat{y}(\mathbf{x}) = \sum_{j=1}^{N_{SV}} \alpha_j K(\mathbf{t}, \mathbf{t}_j) \tag{4}$$

where $\mathbf{t}_j$'s are the support vectors, $\mathbf{t} \in \Re^n$ is $n$-dimensional input vector and $K(\mathbf{t}, \mathbf{t}_j)$ is a Gaussian kernel function given by

$$K(\mathbf{t}, \mathbf{t}_j) = e^{-\frac{\left\|\mathbf{t}-\mathbf{t}_j\right\|}{2\sigma^2}} = e^{-\frac{(t_1-t_{j1})^2+(t_2-t_{j2})^2+\ldots+(t_n-t_{jn})^2}{2\sigma^2}} \tag{5}$$

Then, the input-output relationship becomes

$$\hat{y}(\mathbf{t}) = \sum_{j=1}^{N_{SV}} \alpha_j K(t, t_j) = \sum_{j=1}^{N_{SV}} \alpha_j e^{-\frac{(t_1-t_{j1})^2+(t_2-t_{j2})^2+\ldots+(t_n-t_{jn})^2}{2\sigma^2}} \tag{6}$$

Now, the partial derivatives can be written as

$$\frac{\partial \hat{y}(\mathbf{t})}{\partial \mathbf{t}_k} = \frac{\partial \sum_{j=1}^{N_{SV}} \alpha_j e^{-\frac{(t_1-t_{j1})^2+(t_2-t_{j2})^2+\ldots+(t_n-t_{jn})^2}{2\sigma^2}}}{\partial \mathbf{t}_k} \tag{7}$$

The derivative in Equation (7) can be calculated as

$$\frac{\partial \hat{y}(\mathbf{t})}{\partial \mathbf{t}_k} = \frac{\sum_{j=1}^{N_{SV}} \alpha_j \partial e^{-\frac{(t_1-t_{j1})^2+(t_2-t_{j2})^2+...+(t_n-t_{jn})^2}{2\sigma^2}}}{\partial \mathbf{t}_k} = \sum_{j=1}^{N_{SV}} \alpha_j \frac{\partial e^{-\frac{(t_1-t_{j1})^2+(t_2-t_{j2})^2+...+(t_n-t_{jn})^2}{2\sigma^2}}}{\partial \mathbf{t}_k}$$
$$= \sum_{j=1}^{N_{SV}} \alpha_j \frac{(t_{jk}-t_k)}{\sigma^2} e^{-\frac{(t_1-t_{j1})^2+(t_2-t_{j2})^2+...+(t_n-t_{jn})^2}{2\sigma^2}} = \sum_{j=1}^{N_{SV}} \alpha_j \frac{(t_{jk}-t_k)}{\sigma^2} K(\mathbf{t},\mathbf{t}_j) \tag{8}$$

For a SVR model obtained by the data set $\{\mathbf{t}_i; y_i\}_{i=1}^{i=N_{tr}}$ , it is possible to build a sensitivity vector for the $k^{th}$ input as

$$\mathbf{s}_k = \begin{bmatrix} \frac{\partial \hat{y}(\mathbf{t}_1)}{\partial \mathbf{t}_k} & \frac{\partial \hat{y}(\mathbf{t}_2)}{\partial \mathbf{t}_k} & \cdots & \frac{\partial \hat{y}(\mathbf{t}_N)}{\partial \mathbf{t}_k} \end{bmatrix} \tag{9}$$

Thus, the norm $\|\mathbf{s}_k\|$ of the sensitivity vector can be regarded as a numerical measure that indicates the sensitivity of the output to the $k^{th}$ input for the SVR model obtained by the data set $\{\mathbf{t}_i; y_i\}_{i=1}^{i=N}$ . For large sensitivity of the output to the $k^{th}$ input, we obtain relatively large $\|\mathbf{s}_k\|$ values and vice versa. For (9), $\|\mathbf{s}_k\| = 0$ means no sensitivity to the $k^{th}$ input. Thus, no matter how much the $k^{th}$ input is changed the output is not affected. It is possible to determine the relative sensitivities of the inputs by comparing the sensitivity vectors regarding to all inputs. Moreover, some inputs having very small sensitivities can be discarded from the data set and then the SVR model can be re-obtained with the new data set.

## RESULTS

In order to determine the SVM model parameters, the data set is randomly divided into two parts as training and test set both of which have 569 elements. All input and output data are normalized between [-1;+1] by using the normalization method as follows:

$$x_N = \frac{2(x - x_{min})}{(x_{max} - x_{min})} - 1 \tag{10}$$

where $x$ is the variable to be normalized, $x_{min}$, $x_{max}$ are the minimum and maximum values of $x$ in the data set, respectively, $x_N$ is the normalized output. The error parameters used in the analysis of models are given in Table 2 where $N$ is the number of observations, $R_i$ is the real data and $F_i$ is the forecasting data.

Table 2: Metrics used for the error analyses

| Symbol | Calculation | Definition |
|---|---|---|
| MAE | $\frac{1}{N}\left[\sum_{i=1}^{N}(\lvert R_i - F_i\rvert)\right]$ | Mean Absolute Error |
| RMSE | $\sqrt{\frac{1}{N}\left[\sum_{i=1}^{N}(R_i - F_i)^2\right]}$ | Root Mean Square Error |

### Case -1: Academic Success with GPA

The first analyses are performed on predicting academic success with GPA. The regularization (penalty) parameter (C) is selected as a large constant 10.000. The kernel function is Gaussian, kernel parameter σ is 1.60 and e-tube parameter ε is 0.55 are obtained by grid search in order to minimize the RMSE of the training data. Then RMSE for test data is also calculated as given in Table 3 and the results are given as Figure 1 for the given parameters number of SVs are determined as 73.

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Table 3: Results of Determining of the Kernel Parameters for Case 1

| Training | | Test | | |
|---|---|---|---|---|
| **MAE** | **RMSE** | **MAE** | **RMSE** | **# of SVs** |
| 0.2274 | 0.2676 | 0.2341 | 0.2929 | **73** |

After SVM model is obtained for data prediction, input sensitivity analyses are made. The Pareto analyses of inputs are given in Figure 1(a). As can be seen, the inputs from more sensitive to less are ordered as gender (inp1), PTED score (inp5), high school type (inp4), school registration type (inp6), geographical region (inp3), and age (inp2). Normalized error and support vectors are given in Figure 1(b). Real and predicted data with SVs are given in Figure 1(c).

In order to see the effect of each input on the academic success, the inputs are removed one by one starting from the less sensitive. To avoid the effect of training and test data selection on the analyses, Leave-One-Out Cross-validation is applied. The results are given in Table 4. As can be seen, best training and test performances with less number of support vectors are obtained by using Model #2 in which inp3 and inp2 are removed. When Model #2 is investigated, it is seen that gender, PTED score, high school type and school registration type are taken as input. According to the statistical analysis, it was also concluded that geographical region has no effect on academic success (Basturk et al, 2012). On the other hand gender, high school type, school registration type and PTED score have effect on it. Therefore, it can be concluded that the input sensitivity analysis in Table 4 coincide well with the statistical analysis.

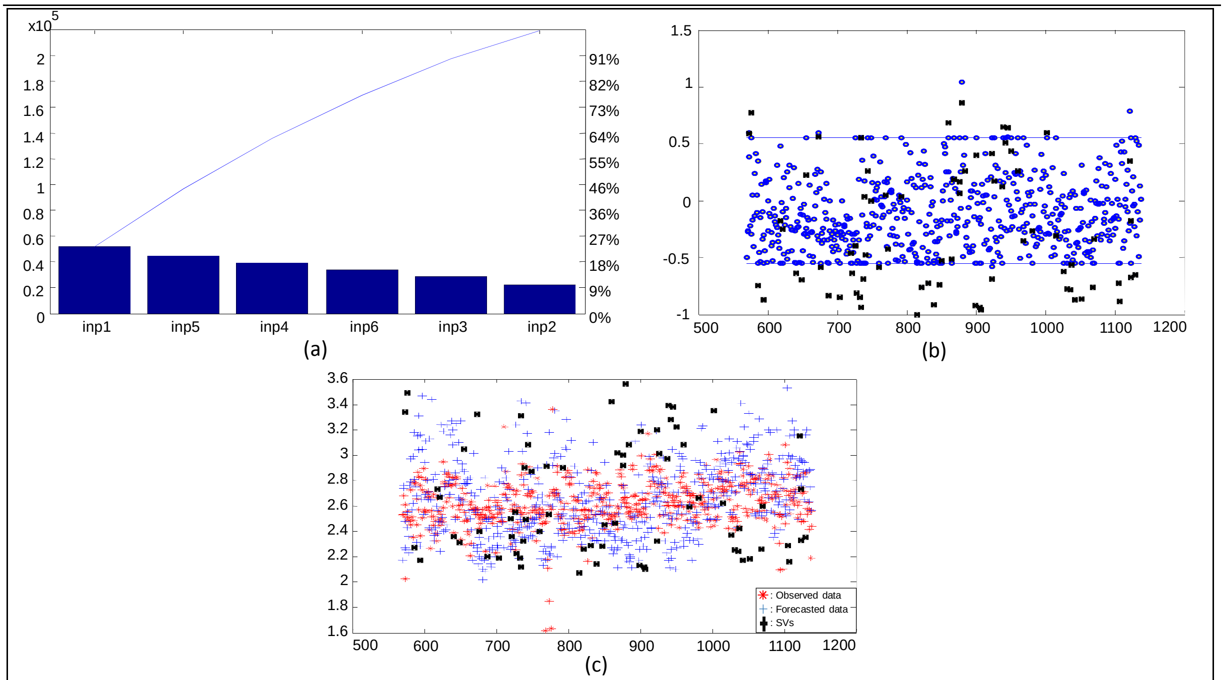


Figure 1: (a) sensitivity analysis Pareto graph, (b) normalized error and support vectors, (c) real and predicted data with SVs for Case 1

Table 4: LOO Cross-Validation Analyses for Case 1

| Model No | Inputs | Training MAE | Training RMSE | Test MAE | Test RMSE | # of SVs |
|---|---|---|---|---|---|---|
| 0 | inp1 inp5, inp4, inp6, inp3, inp2 | 0.2314 | 0.2698 | 0.2433 | 0.2982 | 110 |
| 1 | inp1 inp5, inp4, inp6, inp3 | 0.2237 | 0.2646 | 0.2304 | 0.2797 | 90 |
| **2** | **inp1,inp5, inp4, inp6** | **0.2178** | **0.2595** | **0.2202** | **0.2653** | **74** |
| **3** | **inp1, inp5, inp4** | **0.2211** | **0.2639** | **0.2237** | **0.2702** | **76** |
| 4 | inp1, inp5 | 0.2243 | 0.2687 | 0.2253 | 0.2706 | 81 |
| 5 | inp1 | 0.2481 | 0.2964 | 0.2486 | 0.2974 | 124 |

## Case -2: Graduation Length

The second analyses are performed on predicting with Graduation Length. The regularization (penalty) parameter (C) is also selected as a large constant 10.000. The kernel function is Gaussian, kernel parameter σ is 9.5411 and e-tube parameter ε is 0.1005 are obtained by using *Big Bang-Big Crunch optimization method* in order to minimize the RMSE of the training data. Then RMSE for test data is also calculated as given in Table 5 and the results are given as Figure 2 for the given parameters number of SVs are determined as 357.

Table 5: Results of Determining the Kernel Parameters for Case 2

| Training MAE | Training RMSE | Test MAE | Test RMSE | # of SVs |
|---|---|---|---|---|
| 149.35 | 208.99 | 124.78 | 201.58 | **357** |

The same input sensitivity analysis conducted in Figure 1 and Table 4 for academic success is also obtained for graduation length in Figure 2 and Table 5. Unlike academic success analysis, the inputs from more sensitive to less are ordered as school registration type (inp6), gender (inp1), high-school type (inp4), geographical region (inp3), PTED score (inp5) and age (inp2). And Model 0 is chosen in which all inputs are used. Distinct from Case 1, number of support vectors is very near the number of training samples which means that the SVM model has higher level of complexity and higher over-fitting to the training data.

Table 6: LOO Cross-Validation Analyses for Case 2

| Model No | Inputs | Training MAE | Training RMSE | Test MAE | Test RMSE | # of SVs |
|---|---|---|---|---|---|---|
| **0** | **inp6, inp1, inp4, inp3, inp5, inp2** | **137.88** | **200.88** | **142.94** | **207.99** | **650** |
| **1** | **inp6, inp1, inp4, inp3, inp5** | 145.54 | 212.78 | 148.49 | 216.07 | 656 |
| **2** | **inp6, inp1, inp4, inp3** | 162.28 | 236.24 | 165.03 | 239.11 | 754 |
| **3** | **inp6, inp1, inp4** | 162.19 | 237.01 | 163.63 | 238.44 | 768 |
| **4** | **inp6, inp1** | 162.34 | 237.32 | 162.94 | 237.95 | 767 |
| **5** | **inp6** | 170.21 | 253.83 | 172.55 | 255.44 | 764 |

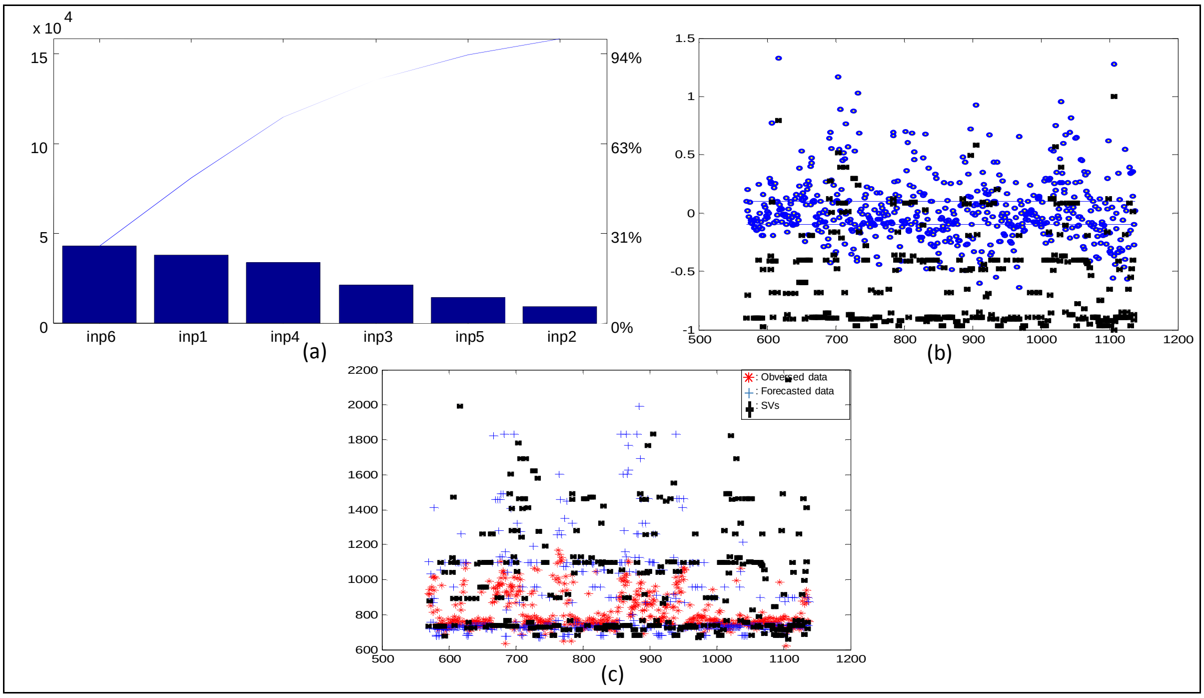

Figure 2: (a) sensitivity analysis Pareto graph, (b) normalized error and support vectors, (c) real and predicted data with SVs for Case 2.

## DISCUSSION AND CONCLUSIONS

In this study, two cases important in terms of education are analyzed. Case 1 is the analyses of academic success and Case 2 is the analyses of the graduation length which also has an economic aspect. By using input sensitivity analyses for the two cases, SVM models having best performance are chosen. Thus, predictions about academic success and graduation length can be made based on newly coming student information using the obtained SVM models. And, the advisors can orient or guide students based on the SVM outputs. It will reduce the workload of the advisor, and help the advisor to make more accurate decisions. At the same time, the obtained SVM model and related outputs can be used to feedback to the infrastructure of the vocational school education system for the provision of some positive developments.

For academic success, gender (inp1), PTED score (inp5), high-school type (inp4) and registration type (inp6) are main factors. Except for gender all other factors are related with academic background of student. It is seen the academic background which is the education taken prior to enrollment to a vocational school has an effect on vocational school success. In the literature it is concluded from the statistical analysis that girls have higher success rates than boys (Basturk et al, 2012). This study has also confirmed the literature. The reason for this phenomenon is the earlier sexual development of girls and thus having more social responsibilities than boys.

In fact, graduation length is another criterion of the academic success. The shorter the student's graduation time, the efficiency of the resources in terms of education and the rate of economic participation will increase. In this respect, it is determined that all the variables registration type (inp6), gender (inp1), high-school type (inp4), geographic region (inp3), PTED score (inp5), age (inp2) in the order given have relative importance on graduation length. As gender, registration type is also one of the essential elements that determine a person's academic background. PTED score and high-school type are important elements of academic history and have an important place in determining the graduation length. In this study, geographic region concept is an interesting determinant and it can be said that culture of region of residence has effect on academic habits and that there are some differences between regions. When it comes to the age factor, it can be said that all students are in the vicinity of average age group. Therefore, age has less effect and sexual development and thus gender has more importance on graduation length. Also, it can be said that students that enroll without examination have negative effect on the motivation of other students, graduation length and academic success.

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